



A study of the relationship between GRACE-TWSA and large-scale atmospheric-oceanic patterns

Babak Vaheddoost & Babak Mohammadi

To cite this article: Babak Vaheddoost & Babak Mohammadi (20 Aug 2025): A study of the relationship between GRACE-TWSA and large-scale atmospheric-oceanic patterns, Hydrological Sciences Journal, DOI: [10.1080/02626667.2025.2537851](https://doi.org/10.1080/02626667.2025.2537851)

To link to this article: <https://doi.org/10.1080/02626667.2025.2537851>



Published online: 20 Aug 2025.



Submit your article to this journal [↗](#)



Article views: 72



View related articles [↗](#)



View Crossmark data [↗](#)



A study of the relationship between GRACE-TWSA and large-scale atmospheric-oceanic patterns

Babak Vaheddoost^a and Babak Mohammadi^b

^aDepartment of Civil Engineering, Bursa Technical University, Bursa, Turkey; ^bHydrology Research Unit, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden

ABSTRACT

This study aims to investigate the connections between changes in the Total Water Storage Anomaly (TWSA) associated with 12 continental/subcontinental regions derived from the Gravity Recovery and Climate Experiment (GRACE) satellite and 25 different Large-Scale Climate Oscillation Indices (LSCOI). Initially, correlation analyses were performed and then the principal component analyses together with wavelet coherent transform were employed in the analyses. The results explain over 50% of TWSA variability, with the Pacific and Indian Oceans exerting strong influence. While Southern Hemisphere regions display consistent long-term relationships with LSCOI patterns, the Northern Hemisphere exhibits more complex dynamics, including trade-offs between leading and lagging effects and in-phase versus anti-phase states. Random Forest and M5 Tree models were then applied using high-correlation LSCOIs as predictors for regional TWSAs. Results of models confirmed the robustness of the identified teleconnections and demonstrated the potential for predicting regional water storage anomalies using climate oscillation indices.

ARTICLE HISTORY

Received 22 October 2024
Accepted 4 July 2025

EDITOR

K. Soulis

ASSOCIATE EDITOR

T. Zhao

KEYWORDS

Climatic oscillation; principal component analyses; remote sensing; wavelet coherent transform

1 Introduction

The availability of terrestrial water plays a key role in various hydrological and climatological processes worldwide (Terrestrial Hydrosphere 2023). Beyond the influence of short-term climatic or meteorological events that affect the dry and wet spells, the presence of water is primarily linked to the significant atmospheric phenomena such as large-scale or long-lasting climate oscillations (Shi *et al.* 2016). Whether driven by droughts/floods or global-scale hydro-climatological changes, it is essential to recognize the substantial influence of major oceanic-atmospheric events on continental water resources. As a result, the interplay and the teleconnection between the water resources and major climate phenomena serves as a compelling motivation for researchers (Burn 2008, Kalra *et al.* 2013, Mohammadi *et al.* 2020).

Previous studies have highlighted the potential of Large-Scale Climate Oscillation Indices (LSCOIs) in understanding water resource dynamics (e.g. Sohrabi *et al.* 2021). Although it is often difficult to clearly distinguish the effects of large-scale teleconnections on water resources, their interdependence and multicollinearity are key challenges in evaluating each index individually (e.g. Chen *et al.* 2014, 2024, Cheng *et al.* 2023, 2024).

Likewise, Sanchez-Rubio *et al.* (2011) examined the influence of predefined LSCOIs, including North Atlantic Oscillation (NAO), Atlantic Multi-decadal Oscillation (AMO), and Pacific Decadal Oscillation (PDO), on riverine systems. The study revealed that streamflow rates in the Mississippi and Pascagoula rivers tend to increase during the positive phase of NAO, while other LSCOIs showed correlations with decreased streamflow. Kuss and Gurdak (2014)

quantitatively assessed the impacts of NAO, PDO, AMO, and El Niño-Southern Oscillation (ENSO) on groundwater levels in the United States. Their findings demonstrated a robust relationship between groundwater levels and oscillations related to ENSO and PDO, while evidence indicated a correspondence between AMO and NAO with variability in groundwater levels.

Wrzesiński and Paluszkiwicz (2011) examined the regional variability of NAO impacts on river discharge across Europe. Their result indicates positive NAO-streamflow correlations in northern Europe, but negative results in the Mediterranean, western France, and south eastern England during winter. Vaheddoost (2017) investigated the teleconnection between NAO, ENSO, AMO, Arctic Oscillation (AO), Indian Ocean Dipole (IOD), Southern Annular Mode (SAM), and PDO on the annual precipitation in Lake Urmia Basin, Iran. It is concluded that ENSO and the PDO oscillations have major effects on the annual precipitations across the basin. The preliminary studies of Vaheddoost (2020) and Mohammadi *et al.* (2020) also showed that the precipitation and relevant droughts across Peru has to do with the major teleconnections around the southern America continent. Similarly, numerous studies have consistently highlighted the significant effects of AMO, PDO, NAO, and ENSO on water resources at a global/regional scale (e.g. Chan and Zhou 2005, Linderholm *et al.* 2011, Zhang *et al.* 2014, Singh *et al.* 2015, Gao *et al.* 2017, Kundzewicz *et al.* 2019, Fathian *et al.* 2021, West *et al.* 2022). Other studies highlighted the role of Pacific Meridional Mode (PMM) on the subtropical north eastern Pacific region, implying that the PMM could exert a notable impact on the ENSO

and global climate (e.g. Zheng *et al.* 2021, 2023, 2024). Recently, Mahmoudi *et al.* (2022) and Akbas and Ozdemir (2023) investigated the role of atmospheric circulations on the hydrological events. Results indicated a meaningful inter-connection between NAO with the rainfall-runoff and the temperature/precipitation events, respectively, in the former and latter study.

The integration of remote sensing with in-situ data has proven to be a viable approach for water and climate studies (Sheffield *et al.* 2018). Among the remote sensing datasets, the Gravity Recovery and Climate Experiment (GRACE) dataset is particularly valuable as it provides information that is not always accessible through traditional in-situ measurements. The GRACE mission consists of a pair of satellites that enable scientists to indirectly estimate the Total Water Storage Anomaly (TWSA) by measuring variations in the Earth's gravity field. This dataset can be used in exploring complex processes related to groundwater, soil moisture, evapotranspiration, ice, droughts, floods, and more. Moreover, GRACE data serves as a powerful tool in understanding ice sheets and glaciers, monitoring global glaciers (e.g. Bringeland and Fotopoulos 2024), examining the interaction between terrestrial water storage and climate variables (e.g. Xie *et al.* 2022, Cho 2024), assessing groundwater stage (e.g. Liu *et al.* 2021, Zhang *et al.* 2021, Benaraba *et al.* 2022, Gorugantula and Kambhammettu 2022), investigating sea level changes (e.g. Yang *et al.* 2024), riverine hydrology (e.g. Yoshe 2024), facilitating flood and droughts (e.g. Khorrami and Gunduz 2021, Li *et al.* 2024), hydro-climatological parameters (e.g. China. Xu *et al.* 2021, Sun *et al.* 2023), and climate change studies (e.g. Tapley *et al.* 2019, Zhou *et al.* 2022).

In this essence, the rate of changes in the terrestrial water and its teleconnection with the LSCOs plays a key role in studying the regional and global water cycle that affect dry and wet spells. By far, several studies have addressed this topic, most of which are focused on the regional cases. Han *et al.* (2019) addressed the TWSA and its link with several climatic factors at Yunnan Province, China. Results indicated a high correlation between TWSA and soil moisture; a downward trend at monthly, seasonal, and annual scales; strong association between precipitation-concentration and TWSA; and widespread extreme drought after 2009, mostly related to AO and ENSO. Guo *et al.* (2021) investigated the link between GRACE based TWSA and 14 climatic indices around the globe. It was concluded that the interaction of tropical cyclones influences both the extent of the response and the delay in changes to land water storage through different parts of the hydrological cycle. Recently, Pereira *et al.* (2024) explored how ENSO affects changes in terrestrial water storage and rainfall in the La Plata Basin. Results showed that the most variations in water storage are connected to extreme climate events like the 2009 drought and are closely related to ENSO phases. The statistical analyses also revealed a strong correlation between major El Niño and La Niña events.

As outlined above, the application of GRACE-TWSA data has been widely employed in diverse hydro-climatological studies. However, no comprehensive investigation has been undertaken yet to examine the phase-space relationship and principal relevance between TWSA data and large-scale oscillation

indices on a global scale. Therefore, the primary objective of this study is threefold: (i) to assess the global connections between continental/subcontinental GRACE-TWSAs and distinct LSCOs at an annual resolution for the first time, (ii) revealing the nature of TWSA oscillations by performing factor analyses, and (iii) to explore the interplay between the phase and antiphase dynamics of the corresponding teleconnections, as well as to evaluate their temporal relevance.

2 Materials and methods

2.1 Study area

This study focuses on examining the teleconnection of average annual GRACE-TWSA data in Amazon (AMZ), Central Asia (CAS), East Asia (EAS), Eastern North America (ENA), Greenland (GRL), North Asia (NAS), Northern Europe (NEU), South Africa (SAF), Southern Australia (SAU), Southern South America (SSA), Western Africa (WAF), and Western North America (WNA), with some major climatic oscillations around the world. The 12 regions (Fig. 1) delineated by Giorgi and Francisco (2000) were selected due to their documented significance in the literature and their pronounced water-related challenges linked to socio-economic and anthropogenic influences at continental and subcontinental scales.

2.2 Large-scale climate oscillation indices (LSCOI)

LSCOs capture recurring and natural climatic patterns that exert significant influences on global precipitation, atmospheric pressure, and sea surface temperature. Scientists have introduced numerous LSCOs to measure the oceanic or atmospheric responses to various climate factors. In this study, we conduct a comprehensive comparison between 25 different LSCOs (outlined in Table 1) and the GRACE-TWSA time series associated with 12 different regions. The selection of these LSCOs was based on criteria such as their accessibility, accuracy, representativeness, and completeness. Table 1, along with Fig. 2, presents detailed information regarding the properties and locations of the chosen LSCOs. To ensure data precision, minimize loss, and address biases related to time lags and periodicity, all the time series are evaluated at annual scales. This approach maintains consistency throughout the analyses and reduces the impact of potential data loss.

It is noteworthy that past studies underlined that different LSCOs are not always independent of each other. For example, preliminary studies by Chen *et al.* (2014, 2024) demonstrated that AO and NPO have significant impacts on the ENSO; while Cheng *et al.* (2023, 2024) showed that the AO has a significant impact on the Indian Ocean Dipole (IOD). Therefore, one shall be aware of limitations in the application of those indices simultaneously and the problem that may arise due to this fact.

2.3 GRACE-TWSA data

The extraction of TWSA data involves processing monthly gravity changes and their corresponding Earth's surface mass changes to eliminate correlated and random errors, as well as

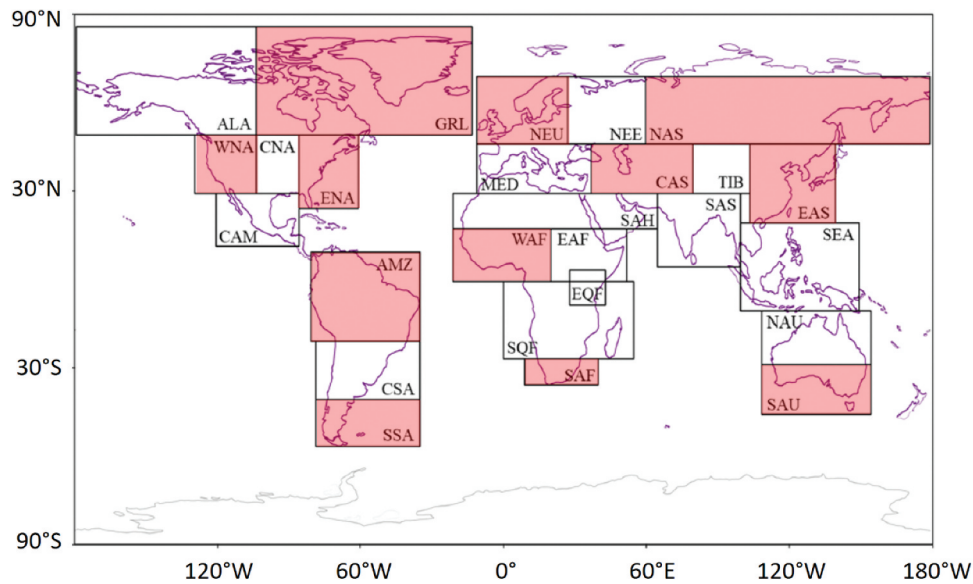


Figure 1. The selected continental and subcontinental regions in the analyses. Indicating: Amazon (AMZ), Central Asia (CAS), East Asia (EAS), Eastern North America (ENA), Greenland (GRL), North Asia (NAS), Northern Europe (NEU), South Africa (SAF), Southern Australia (SAU), Southern South America (SSA), Western Africa (WAF), and Western North America (WNA) regions, as reported by Giorgi and Francisco (2000).

Table 1. LSCOs used and the associated details used in the study.

Index	Full Name	About	Reference
ALBSA	Aleutian Low - Beaufort Sea Anticyclone	Captures the variability in the North Pacific/Pacific Arctic tropospheric circulation	Cox <i>et al.</i> (2019)
AMM	Atlantic Meridional Mode	The cross-equatorial meridional difference in sea surface temperature anomaly in the tropical Atlantic	Chiang and Vimont (2004), Doi <i>et al.</i> (2010)
AO	Arctic Oscillation	The back-and-forth shifting of atmospheric pressure between the Arctic and the mid-latitudes of the North Pacific and North Atlantic	Zhou <i>et al.</i> (2001)
EA/WR	Eastern Asia/ Western Russia	Characterized by large-scale anomalies over the Caspian Sea toward western Europe	Barnston and Livezey (1987)
EP/NP	East Pacific/North Pacific Oscillation	The spring-Summer-Fall pattern focused on three anomaly centers	Li <i>et al.</i> (2015)
IOD	Indian Ocean Dipole	Anomalous SST gradient between the western equatorial Indian Ocean (50E-70E and 10S-10N) and the south eastern equatorial Indian Ocean (90E-110E and 10S-0N).	Kumar <i>et al.</i> (2020)
NAO	North Atlantic Oscillations	The difference in normalized pressure between Iceland and the Azores	Hurrell (1995)
Niño 1+2	Extreme Eastern Tropical Pacific SST	The average sea surface temperature between 0° ~ 10° S and 90° W ~ 80° W	Rayner <i>et al.</i> (2003)
Niño 3	Eastern Tropical Pacific SST	The average sea surface temperature between 5° S ~ 5° N and 150° W ~ 90° W	Rayner <i>et al.</i> (2003)
Niño 3.4	East Central Tropical Pacific SST	The average sea surface temperature between 5° S ~ 5° N and 170° W ~ 120° W	Rayner <i>et al.</i> (2003)
Niño 4	Central Tropical Pacific SST	The average sea surface temperature between 5° S ~ 5° N and 160° E ~ 150° W	Rayner <i>et al.</i> (2003)
NOI	Northern Oscillation Index	The difference in sea level pressures between Darwin in Australia and the North Pacific High	Schwing <i>et al.</i> (2002)
NP	North Pacific pattern	Sea level differences between 30° N ~ 65° N and 160° E ~ 145° W	Trenberth and Hurrell (1994)
ONI	Oceanic Niño Index	The 3-month average sea surface temperatures in the east-central tropical Pacific (120°-170°W) near the International Dateline	Glantz and Ramirez (2020)
PDO	Pacific Decadal Oscillation	The temporal covariance matrix of sea surface temperature in the Pacific	Mantua <i>et al.</i> (1997)
PMM	Pacific Meridional Mode	Describes the meridional variability in the tropical Pacific Ocean	Chiang <i>et al.</i> (2004)
PNA	Pacific North American index	Anomalies in the geopotential height fields of 700 or 500 mb over the western and eastern US	Barnston and Livezey (1987)
QBO	Quasi-Biennial Oscillation	A quasiperiodic oscillation between easterlies and westerlies of the equatorial zonal wind in the tropical stratosphere	Baldwin <i>et al.</i> (2001)
SAM	Southern Annular Mode	Zonal pressure difference between the latitudes of 40S and 65S	Schneider <i>et al.</i> (2013)
SOI	Southern Oscillation Index	The difference between normalized pressure in Tahiti and Darwin	Ropelewski <i>et al.</i> (1987)
TNA	Tropical Northern Atlantic index	Sea surface temperatures between 15° W ~ 57.5° W and 5.5° N ~ 23.5° N	Enfield <i>et al.</i> (1999)
TNI	Trans-Niño Index	The difference between normalized anomalies of sea surface temperature between Niño 1+2 and Niño 4	Trenberth and Stepaniak (2001)
TSA	Tropical Southern Atlantic index	Sea surface temperatures between 30°W ~ 10°E and 20°S ~ 0°	Enfield <i>et al.</i> (1999)
WHWP	Western Hemisphere Warm Pool	The sea surface anomaly (when it is hotter than 28.5° C) in the eastern North Pacific and Atlantic oceans	Wang and Enfield (2001)
WP	Western Pacific Index	low-frequency oscillations over the North Pacific	Yang <i>et al.</i> (2017)

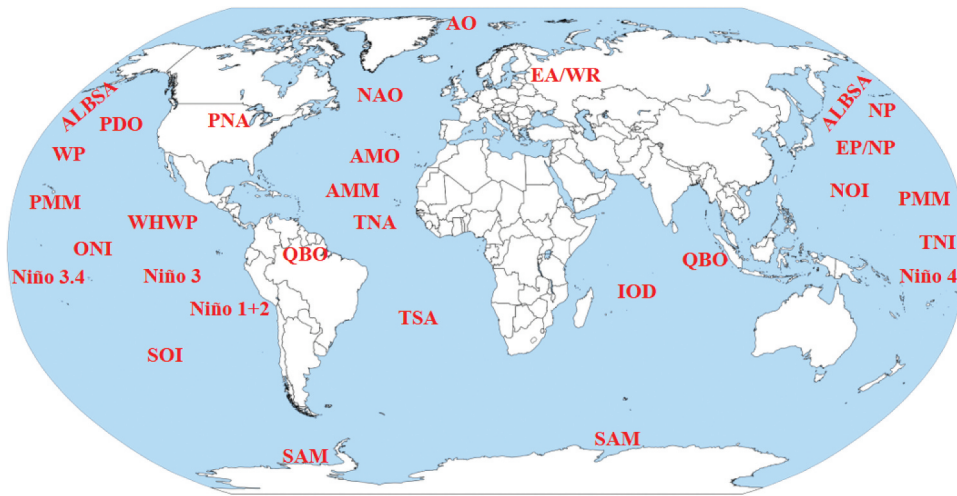


Figure 2. Approximate locations of LSCOs used in this study.

other adjustments. Several corrections have been applied to the GRACE-TWSA data, including glacial isostatic adjustment (GIA) and glacial mass balance, atmospheric pressure, and ocean tides.

Initially, the GRACE data is obtained using the Mascon (mass concentration) solution technique. Mascons provide estimates of mass changes over predefined small regions, capturing the temporal movement of water content. The Jet Propulsion Laboratory (JPL) processes the data using 3° equal-area Mascons (RL06 V02 with CRI) sampled on a 0.5° grid for the period between April 2002 and August 2021 (10.5067/TEMSC-3JC62).

In this study, the annual TWSA time series is determined by averaging the monthly rates from the initial time series. This approach aims to minimize precision errors (i.e. using average values to smooth the time series) and data loss associated with the LSCOs. To manage the temporal gaps within the GRACE/GRACE-FO datasets, our study applied a Linear Temporal Interpolation (LTI) method. This method was selected for its simplicity and effectiveness in estimating missing values in time series data, where it assumes that changes between consecutive data points occur at a constant rate. The LTI method involves calculating the rate of change between available data points immediately before and after the missing period. By applying this rate of change linearly, we can estimate the missing values with reasonable accuracy. This approach is particularly suitable for the GRACE/GRACE-FO datasets, where the time series reflects gradual changes in Earth's water storage and allows for the assumption of linearity over short intervals. For periods where multiple consecutive dates were missing, we employed a piecewise linear interpolation strategy, breaking the series into segments where data were available and applying the LTI method within each segment. This approach minimizes the potential for error accumulation over longer gaps and maintains the integrity of the dataset's temporal pattern. It should be noted that our analyses incorporate GRACE data spanning April 2002 to June 2017, followed by GRACE-FO data from June 2018 onwards.

2.4 Principal component analyses (PCA)

PCA is a technique employed to reduce the dimensionality of data samples and transform its basis. It allows for the examination of a smaller set of variables in practice, revealing similarities or differences among the principal components (or factors) by disregarding less significant components. In the present study, both the independent variables, designated as LSCOs, and the dependent variable, denoted as GRACE-TWSA, are subjected to PCA within a structured dataset, or matrix, to discern the respective eigenvalue–eigenvector pairs, statistically independent of each other. These pairs, derived from the covariance matrix, serve to elucidate pivotal factors inherent in the dataset. Conventionally, the eigenvectors delineate the orientations of the axes corresponding to the areas where the majority of data volatility is concentrated, thus constituting the principal components. Conversely, the eigenvalues represent scalar coefficients associated with eigenvectors, quantifying the magnitude of variance encapsulated within each principal component. The number of factors, however, typically is equal to or less than the number of initial variables.

Assuming that the number of variables and independent factors are less or the same, PCA helps in assessment of classification and identification of the significant relationships between the two datasets. The correlation between a variable and the corresponding variability explained by the factor is then utilized to determine the most representative factor when the number of factors or principal components is equal to or fewer than the number of variables. Ultimately, the factors that exhibit the highest interconnections with the variables and explain the greatest amount of variability between LSCOs and TWSA are employed for dimensional reduction and relationship analyses. The interested reader may refer to the typical statistical handbooks, software tutorial (e.g. SPSS or MATLAB), technical websites (e.g. <https://www.ibm.com/topics/principal-component-analyses>), or the statement of the art such as the preliminary studies of Ringnér (2008) and Greenacre *et al.* (2022).

Subsequently, PCA analysis was performed to identify and extract two major components (i.e. independent factors) that effectively capture significant disturbances (i.e. variances) among the selected variables (i.e. LSCOs and TWSAs). These factors are then utilized to interpret the inter- or intra-phase relationships within the dataset. Furthermore, inter-relationship diagrams are employed along with the variance explained by the analyses to identify coherent and opposing patterns. These patterns can be further examined and evaluated to gain valuable insights and inform decision-making processes.

2.5 Wavelet coherent transformation (WCT)

In essence, a wavelet can be regarded as a function with zero mean, utilized to analyse the trade-off between localization in the time and frequency domains. The Wavelet Coherent Transform (WCT), similar to cross wavelet transformations (Morlet *et al.* 1982), allows for separate representations of the phase and anti-phase components of spectra (<https://github.com/grinsted/wavelet-coherence>). Thus, the cross-spectrum of the WCT identifies the time-localization of the common oscillatory behaviour of the allocated time series. Torrence and Compo (1998) discovered that coherence and phase lags between two signals vary across both frequency and time within the study domain. As a result, the WCT becomes a valuable tool for identifying localized correlation coefficients in the time-frequency domain.

The generation of the WCT involves employing Monte Carlo realizations to represent the relationship between the two signals. To conceptualize the impact of red noise, attenuation of persistence, significant correlations, and the direction of leading and/or lagging in the phase space, certain visual elements are utilized. These include a magnitude bar, a significant cone to reduce noise effects (depicting with a blurred area), a predefined area for identifying significant correlations, and representative arrows. The resulting spectra can be subsequently interpreted, with the horizontal and vertical axes representing time and frequency (associated with each time series), the magnitude bar and corresponding colours indicating the degree of correlation, the cone highlighting noise reduction, the predefined area identifying significant correlations, and the arrows depicting the phase state. The direction of the arrows, whether pointing right or left, signifies in-phase and anti-phase relationships, while downward and upward arrows represent leading and lagging effects, respectively. For instance, a downward arrow slightly pointing to the left indicates anti-phase lags, while an arrow pointing to the right signifies an in-phase connection with zero lags.

The interested reader may refer to the preliminary studies of Torrence and Webster (1999), Grinsted *et al.* (2004), or Maraun *et al.* (2007) for more information regarding the application of wavelet coherence.

2.6 Applicability of the results in model development

One of the primary objectives of conducting such analyses (i.e. correlation, PCA, and WCT) is to establish a robust

foundation for the application of more advanced analytical and predictive/descriptive models. Given that any model seeks to justify its structure by ensuring the presence of a substantive relationship between dependent and independent variables, a well-fitted model can serve as a crucial validation mechanism for the preliminary analyses of the dataset. In this context, we employed the well-established Random Forest (RF; Breiman 2001) and M5Tree (M5T; Quinlan 1992, 1993) models to justify the applicability of the determined results in model development.

To support the teleconnection analyses, RF and M5T models were applied using only the LSCOs with strong correlations ($|r| \geq 0.5$, depending on the region) as predictors of regional TWSA, thereby maintaining model parsimony and emphasizing the dominant climate oscillation influences. Consequently, by assessing the correlation coefficient (r), Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE), we evaluated the reliability and consistency of our analyses in developing the RF and M5T models.

The RF is an ensemble learning method that operates by constructing multiple decision trees during training and outputting the mean prediction of the individual trees for regression problems (Breiman 2001). In our implementation, we used 500 trees with proximity measures enabled to enhance model stability while capturing complex non-linear relationships between LSCOs and TWSA. The model's robustness to outliers and ability to handle high-dimensional data make it particularly suitable for climate teleconnection studies where interactions are often complex and non-linear. The M5T model, originally proposed by Quinlan (1992, 1993), combines the strengths of decision trees with linear regression models at the leaf nodes. Unlike conventional regression trees, M5T constructs piecewise linear models rather than constant values at the terminal nodes, allowing for more nuanced modelling of the relationship between predictors and response variables. Our implementation utilized the Cubist package in R (Kuhn *et al.* 2025), configuring the model with 10 committees and 100 rules to adequately capture the varying relationships between climate oscillations and water storage anomalies across different regions. For model evaluation, we employed a randomized data partitioning approach in each region, systematically dividing the annual-scale dataset into distinct training and testing subsets (13 years for training and 6 years for testing) to ensure robust assessment of the models' predictive capabilities across different hydro-climatic conditions.

2.7 Applied workflow

Figure 3 summarises the methodology employed in this study. The first step involves comparing the LSCOs and GRACE-TWSA in the selected regions using the simple correlation coefficient (r). The r is a measure that evaluates the degree of linear dependence between variables; while $|r| \leq 0.19$, $\pm 0.2 \leq r \leq \pm 0.39$, $\pm 0.4 \leq r \leq \pm 0.59$, $\pm 0.6 \leq r \leq \pm 0.79$, and $\pm 0.8 \leq r \leq \pm 1.0$ roughly indicate very low, low, moderate, high, and very high correlation of direct (+) or

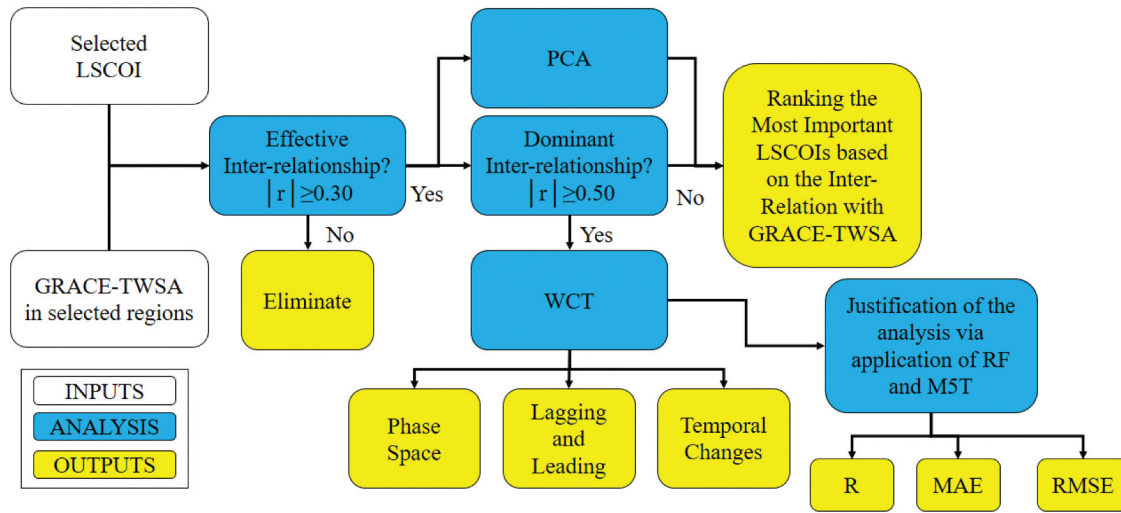


Figure 3. Flowchart of the applied methodology.

reverse (–) nature, respectively. In our study, however, correlation coefficients of approximately 0.3 and 0.5 are interpreted as thresholds for identifying effective and dominant relationships, respectively, between terrestrial water storage and climate indices. This interpretation aligns with established statistical conventions, where a coefficient around 0.3 signifies a moderate association, and values near 0.5 or higher denote strong associations. Such thresholds are particularly pertinent in complex environmental systems, where multiple interacting factors often result in modest correlation values that still reflect meaningful physical relationships (e.g. Okay Ahi and Jin 2019, Afamondji *et al.* 2025). Therefore, LSCOIs with $|r| \leq 0.3$ are considered ineffective and subsequently eliminated. Afterward, a criterion of $|r| \geq 0.5$ is applied to investigate whether the inter-relationship can be classified as dominant. All effective inter-relationships are utilized in the PCA, while the dominant inter-relationships are further employed in the WCT application. Following the initial analyses, the inter-relationship between LSCOIs and GRACE-TWSA in the selected regions undergoes a comprehensive phase-space analysis. This includes examining the temporal changes in the time series, investigating the lagging and leading effects of the inter-relationship, and ranking the relationships based on the degree of correlation. Finally, the RF and M5T models were employed to validate the significance of identified teleconnections between LSCOIs and regional TWSA, providing quantitative confirmation of the relationships established through correlation, PCA, and wavelet analyses.

3 Results

3.1 Correlation analyses

Initially, the correlation coefficients between the selected regions and LSCOIs were assessed. The extent of these relationships is outlined in Table 2, where correlations with $|r| \geq 0.30$ were deemed effective for further analyses and PCA (*italic* values in Table 2). According to Table 2, all of the continental/sub

continental regions showed teleconnection with several LSCOIs. Yet, the dominant teleconnections (i.e. $|r| \geq 0.50$) are limited to AMM and IOD with CAS region; Niño 4, SOI, EP/NP, and TNI with EAS region; WHWP, TSA, IOD, ALBSA, and PMM with ENA region; WHWP and IOD with GRL, NEU, and SAF regions; PDO with SSA region; IOD and ALBSA with WAF region; and finally PDO, Niño 4, AMM, IOD, and PMM with WNA region (**bold** values in Table 2). In this regard, the most frequent teleconnections are established between IOD and WHWP with the continental/sub-continental regions. It is also shown that the ENA and WNA with the highest number of dominant teleconnection, and AMZ, SAU, and NAS with no sign of dominant teleconnections defines the diversity of the great picture. Hence, oceanic oscillations, particularly in the Pacific and the Indian Ocean, are closely associated with nearly all patterns worldwide. The correlation coefficients presented in Table 2 indicate the strength of the linear relationship between GRACE-TWSA and LSCOIs. Further analyses show that the Niño 4 partially near Australian coasts is more effective than the Niño 1 + 2, Niño 3, and Niño 3.4. As observed from the correlation analyses, regions in close proximity to the Pacific and Indian Oceans are more susceptible to the influence of these LSCOIs. Therefore, changes in terrestrial water content in these regions can be associated with climatic patterns that directly or indirectly impact precipitation, evaporation, temperature, and moisture dynamics.

3.2 Principal components analyses

As detailed previously, the two-factor PCA was conducted, capturing over 50% of the total variance associated with the connections between the selected LSCOIs and GRACE-TWSA pairs. Comprehensive details regarding the factors and the corresponding variance explained by each are presented in Table 3 and Fig. 4, facilitating a more precise interpretation of climatic teleconnections. In most cases, Factor 1 effectively accounts for at least 30% of the total heteroscedasticity within the solution domain (shaded cells in Table 3). Accordingly, the proportion of total variance

Table 2. Correlation matrix between GRACE-TWSA and LSCOI indices (*italic* and **bold** values in the table defines effective, and dominant correlations, respectively).

	AMZ	SAU	CAS	EAS	ENA	GRL	NAS	NEU	SAF	SSA	WAF	WNA
ALBSA	0.288	0.191	<i>-0.469</i>	-0.264	0.513	<i>-0.404</i>	0.150	<i>-0.382</i>	<i>0.401</i>	0.044	0.501	-0.245
AMM	0.096	0.208	0.547	-0.069	<i>-0.385</i>	<i>0.331</i>	-0.069	<i>0.335</i>	-0.238	-0.195	<i>-0.381</i>	0.658
AO	0.095	0.186	<i>-0.357</i>	-0.236	<i>0.305</i>	<i>-0.306</i>	<i>0.304</i>	-0.260	<i>0.303</i>	-0.056	<i>0.363</i>	-0.167
EA/WR	0.072	-0.180	-0.069	-0.083	0.019	0.084	0.106	0.091	-0.110	-0.039	0.040	-0.081
EP/NP	<i>-0.253</i>	<i>-0.345</i>	-0.108	0.503	0.188	0.002	0.179	0.017	<i>-0.045</i>	<i>0.476</i>	<i>-0.037</i>	<i>-0.436</i>
IOD	<i>-0.076</i>	0.160	-0.720	0.029	0.828	-0.765	0.153	-0.740	0.761	0.115	0.745	-0.615
NAO	<i>-0.075</i>	0.079	<i>-0.358</i>	-0.013	<i>0.321</i>	-0.260	0.255	-0.223	0.242	0.209	0.264	<i>-0.445</i>
Niño 1 + 2	0.021	0.110	<i>-0.300</i>	-0.040	0.223	-0.224	0.064	-0.206	0.243	0.103	0.199	-0.255
Niño 3	-0.171	-0.154	-0.178	0.244	0.227	-0.092	0.059	-0.071	0.075	0.241	0.050	<i>-0.391</i>
Niño 3.4	<i>-0.320</i>	-0.269	-0.139	<i>0.399</i>	0.248	-0.070	0.117	-0.043	0.050	<i>0.373</i>	0.009	<i>-0.455</i>
Niño 4	<i>-0.396</i>	<i>-0.338</i>	-0.165	0.515	<i>0.328</i>	-0.118	0.195	-0.085	0.091	<i>0.448</i>	0.050	-0.541
NOI	0.233	0.096	-0.078	-0.222	0.128	-0.162	<i>0.458</i>	-0.125	0.149	<i>-0.302</i>	0.166	0.019
NP	<i>0.403</i>	0.180	<i>-0.364</i>	<i>-0.304</i>	0.245	<i>-0.322</i>	-0.121	<i>-0.338</i>	0.222	<i>-0.486</i>	<i>0.432</i>	-0.083
ONI	<i>-0.324</i>	-0.276	-0.113	<i>0.395</i>	0.226	-0.045	0.113	-0.019	0.031	<i>0.389</i>	-0.019	<i>-0.440</i>
PDO	<i>-0.452</i>	-0.215	-0.212	<i>0.496</i>	<i>0.440</i>	-0.243	0.292	-0.205	0.291	0.576	0.134	-0.546
PMM	<i>-0.329</i>	-0.204	<i>-0.402</i>	<i>0.446</i>	0.648	<i>-0.426</i>	<i>0.355</i>	<i>-0.382</i>	<i>0.406</i>	<i>0.409</i>	<i>0.363</i>	-0.704
PNA	<i>-0.364</i>	-0.295	0.266	0.087	-0.101	0.144	0.274	0.158	-0.057	<i>0.312</i>	-0.252	0.016
QBO	-0.032	-0.074	-0.114	0.113	0.176	-0.079	0.176	-0.057	0.075	0.139	0.081	-0.034
SAM	0.104	<i>0.357</i>	-0.223	-0.029	0.196	-0.290	-0.096	-0.293	<i>0.310</i>	-0.281	0.254	-0.153
SOI	<i>0.365</i>	<i>0.377</i>	0.004	-0.520	-0.192	0.005	-0.212	-0.032	0.040	<i>-0.378</i>	0.077	<i>0.380</i>
TNA	-0.052	0.134	<i>0.328</i>	0.089	-0.118	0.116	-0.035	0.130	-0.039	-0.155	-0.165	<i>0.420</i>
TNI	<i>0.495</i>	<i>0.494</i>	-0.065	-0.631	-0.117	-0.093	-0.133	-0.108	0.135	<i>-0.450</i>	0.126	<i>0.379</i>
TSA	-0.207	-0.197	<i>-0.429</i>	0.098	0.508	<i>-0.384</i>	0.046	<i>-0.392</i>	<i>0.384</i>	0.209	<i>0.432</i>	<i>-0.447</i>
WHWP	-0.259	0.144	<i>-0.400</i>	<i>0.326</i>	0.592	-0.531	0.011	-0.512	0.556	0.055	<i>0.423</i>	<i>-0.440</i>
WP	-0.071	-0.226	<i>0.393</i>	-0.001	-0.112	0.287	0.242	<i>0.306</i>	-0.210	0.101	<i>-0.350</i>	0.172

Table 3. The conducted PCA between TWSA and LSCOI indices (in the table shaded cells indicate the most relevant factor with highest correlation rate between TWSA and LSCOI, while * denotes elimination of the parameter by PCA due to the lack of relationship).

	AMZ		SAU		CAS		EAS		ENA		GRL		NAS		NEU		SAF		SSA		WAF		WNA	
PC	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2
Variance Exp. (%)	59.5	13.1	61.5	20.4	32.4	16.9	62.3	11.7	41.7	19.5	42.8	21.7	52.4	22.4	40.9	18.7	44.1	22.3	56.6	12.6	38.6	19.4	49.9	16.2
Region	-0.5	-0.1	-0.5	0.6	-0.9	-0.1	0.6	-0.1	0.8	0.1	-0.9	-0.1	0.7	0.2	-0.9	0.1	0.9	-0.1	0.6	0.4	0.9	-0.1	-0.7	-0.4
ALBSA	*	*	*	*	0.6	-0.5	*	*	0.5	0.6	0.6	-0.6	*	*	0.5	0.7	0.5	0.7	*	*	0.6	-0.5	*	*
AMM	*	*	*	*	-0.8	0.1	*	*	-0.6	-0.1	-0.6	0.1	*	*	-0.6	-0.1	*	*	*	*	-0.6	0.1	-0.7	-0.2
AO	*	*	*	*	0.5	-0.6	*	*	0.3	0.8	0.5	-0.6	0.8	-0.4	*	*	0.4	0.6	*	*	0.5	-0.6	*	*
EA/WR	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
EP/NP	*	*	0.9	0.3	*	*	0.9	-0.2	*	*	*	*	*	*	*	*	*	*	0.9	-0.2	*	*	*	*
IOD	*	*	*	*	0.8	0.3	*	*	0.8	-0.1	0.9	0.2	*	*	0.9	-0.1	0.9	-0.1	*	*	0.9	0.3	0.4	0.8
NAO	*	*	*	*	0.4	-0.6	*	*	0.4	0.6	*	*	*	*	*	*	*	*	*	*	*	*	0.2	0.1
Niño 1 + 2	*	*	*	*	0.4	0.3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Niño 3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	0.9	-0.2
Niño 3.4	0.9	-0.3	*	*	*	*	0.9	-0.1	*	*	*	*	*	*	*	*	*	*	0.9	-0.2	*	*	0.9	-0.2
Niño 4	0.9	-0.2	0.9	0.4	*	*	0.9	-0.1	0.6	-0.3	*	*	*	*	*	*	*	*	0.9	-0.2	*	*	0.9	-0.2
NOI	*	*	*	*	*	*	*	*	*	*	*	*	0.9	-0.3	*	*	*	*	-0.2	-0.5	*	*	*	*
NP	*	*	*	*	0.3	-0.4	-0.6	0.2	*	*	0.4	-0.7	*	*	0.3	0.8	*	*	-0.6	-0.6	0.4	-0.7	*	*
ONI	0.9	-0.3	*	*	*	*	0.9	-0.1	*	*	*	*	*	*	*	*	*	*	0.9	-0.2	*	*	0.9	-0.3
PDO	0.9	0.1	*	*	*	*	*	*	0.8	-0.3	*	*	*	*	*	*	*	*	0.9	0.1	*	*	0.8	0.2
PMM	0.7	0.1	*	*	0.7	0.2	0.7	0.5	0.9	-0.1	0.7	0.4	0.5	0.8	0.7	-0.3	0.7	-0.1	0.6	-0.2	0.7	0.4	0.7	0.5
PNA	0.4	0.8	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	0.4	0.7	*	*	*	*
QBO	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
SAM	*	*	-0.5	0.7	*	*	*	*	*	*	*	*	*	*	*	*	0.2	-0.6	*	*	*	*	*	*
SOI	-0.9	0.1	-0.9	0.3	*	*	-0.9	0.1	*	*	*	*	*	*	*	*	*	*	-0.9	0.1	*	*	-0.9	0.4
TNA	*	*	*	*	-0.4	0.2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	-0.4	0.2
TNI	-0.7	0.1	-0.9	0.2	*	*	-0.7	0.4	*	*	*	*	*	*	*	*	*	*	-0.7	0.2	*	*	-0.6	0.2
TSA	*	*	*	*	0.6	0.3	*	*	0.5	0.1	0.7	-0.1	*	*	0.7	0.2	0.7	0.1	*	*	0.7	0.1	0.1	0.8
WHWP	*	*	*	*	0.4	0.8	0.4	0.8	0.6	-0.7	0.5	0.8	*	*	0.6	-0.6	0.6	-0.7	*	*	0.4	0.8	0.4	0.5
WP	*	*	*	*	-0.1	0.1	*	*	*	*	*	*	*	*	-0.1	-0.1	*	*	*	*	-0.1	0.1	*	*

explained for AMZ, SAU, CAS, EAS, ENA, GRL, NAS, NEU, SAF, SSA, WAF, and WNA are 72.5%, 81.9%, 49.3%, 73.9%, 61.1%, 64.5%, 74.9%, 59.6%, 66.4%, 69.2%, 57.9%, and 66.2%, respectively. Thus, the two-factor analyses for the CAS region (49.3%) and the SAU region (81.9%) suggest that the proposed framework captures a relatively reliable proportion of the total variance (i.e.

events) in the dataset. According to Table 3, almost all regions except SAU exhibit strong concordance with the first factor. Furthermore, the correlation between LSCOIs and GRACE-TWSA pairs underscores the significant influence of Pacific and Indian Oceans' patterns on terrestrial water storage worldwide. Notably, the QBO oscillation near the Indian Ocean and the EA/WR pattern on the

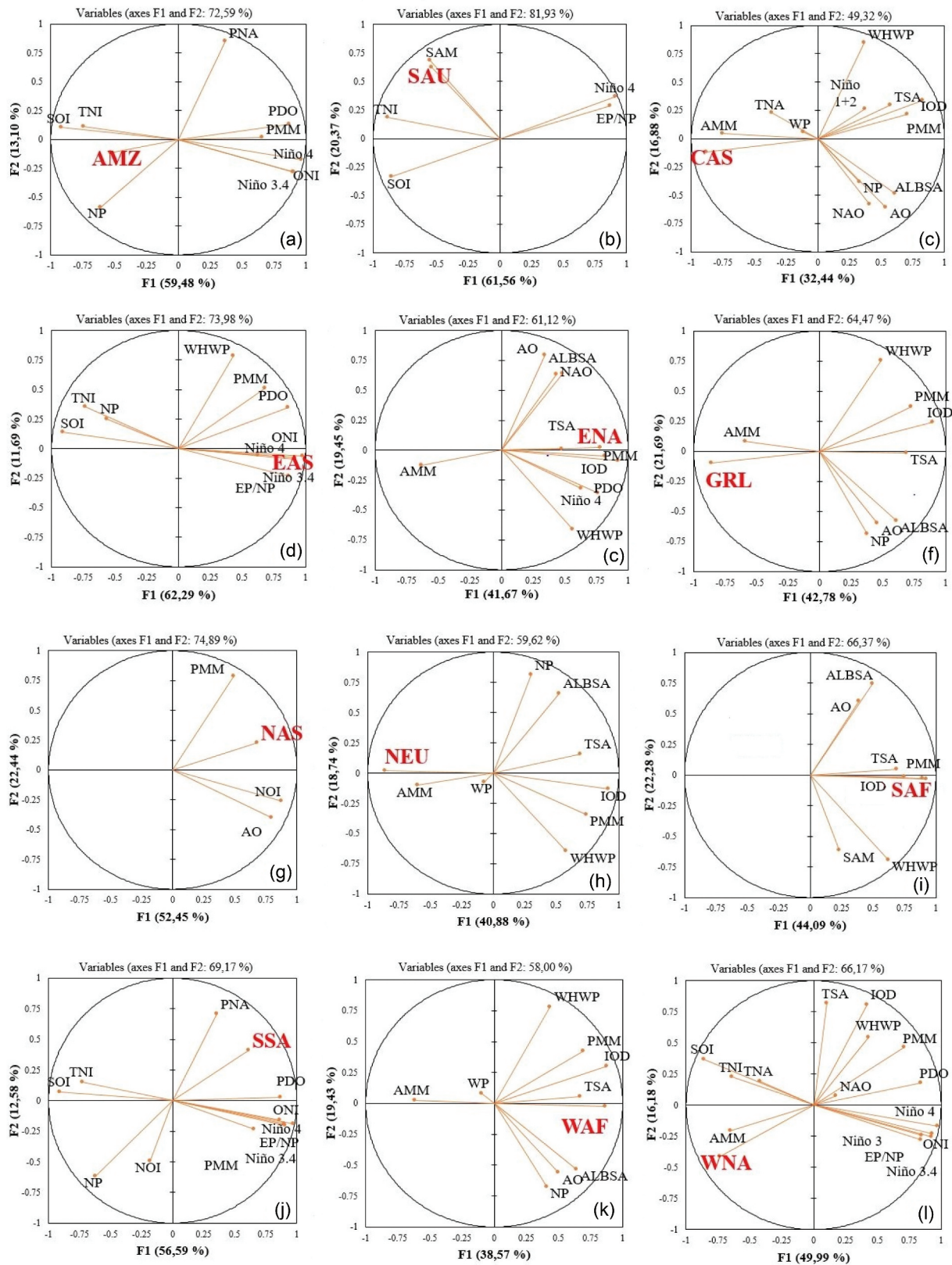


Figure 4. Inter-relationship of the selected variables with the first and second factors (PCA) and their correspondence with the (a) AMZ, (b) SAU, (c) CAS, (d) EAS, (e) ENA, (f) GRL, (g) NAS, (h) NEU, (i) SAF, (j) SSA, (k) WAF, and (l) WNA regions.

Asian continent showed no significant association with the factors employed in the analyses. As illustrated in Fig. 4, most LSCOs (except for SAU and SSA) demonstrate

a higher correlation and factor loadings with at least one of the identified factors, thereby reinforcing the assumption of independence in the analyses.

3.3 Phase space analyses

Once the effective ($|r| \geq 0.3$) and the dominant ($|r| \geq 0.5$) LSCOI indices were recognized for each region, the most dominant LSCOIs associated with the selected regions underwent separate WCT analyses. The findings are presented in Fig. 5, showcasing the time-frequency separation, significant cone, degrees of significance, attenuation of persistence, and the projection of the teleconnection phase-space. These visualizations provide insights into the temporal changes in teleconnections, while the evaluation of the projected results in blurred-zones should be avoided mostly due to the uncertainty and insignificance. When examining the teleconnections particularly between CAS-AMM (Fig. 5a), CAS-IOD (Fig. 5b), EAS-Niño 4 (Fig. 5d), EAS-SOI (Fig. 5e), EAS-TNI (Fig. 5f), ENA-ALBSA (Fig. 5g), WNA-IOD (Fig. 5v), WNA-Niño 4 (Fig. 5w), and WNA-PDO (Fig. 5x) the magnitude of teleconnection at low frequency (i.e. large-scale cycles) are initially dominated (i.e. prior to year 2012). However, after the year 2012 (i.e. the second half of the study period), mid- or high-frequency (i.e. small cycles) oscillations took precedence in the phase-space. Conversely, in the inter-relation between EAS-EP/NP (Fig. 5c) and WNA-AMM (Fig. 5u) pairs, high frequencies consistently exerted their influence, while mid-frequency oscillations exhibited more consistency. In this illustration, the magnitude of the teleconnections between CAS-AMM (Fig. 5a), CAS-IOD (Fig. 5b), EAS-EP/NP (Fig. 5c), EAS-Niño 4 (Fig. 5d), EAS-SOI (Fig. 5e), EAS-TNI (Fig. 5f), ENA-ALBSA (Fig. 5g), NEU-IOD (Fig. 5n),

WAF-ALBSA (Fig. 5s), WNA-IOD (Fig. 5v), WNA-Niño 4 (Fig. 5w), and WNA-PDO (Fig. 5x) pairs is at peak showcasing the significance of the teleconnections at decadal (10 years) level. The direction of the arrows, however, shows in-phase relations (i.e. arrows pointing to the right) between CAS-AMM (Fig. 5a), EAS-ENNP (Fig. 5c), EAS-Niño 4 (Fig. 5d), ENA-IOD (Fig. 5h), ENA-PMM (Fig. 5i), ENA-TSA (Fig. 5j), SAF-IOD (Fig. 5p), SAF-WHWP (Fig. 5q), SSA-PDO (Fig. 5r), WAF-ALBSA (Fig. 5s), WAF-IOD (Fig. 5t), and WNA-AMM (Fig. 5u) pairs; and anti-phase relation (i.e. arrows pointing to the left) between CAS-IOD (Fig. 5b), EAS-SOI (Fig. 5e), EAS-TNI (Fig. 5f), ENA-ALBSA (Fig. 5g), GRL-IOD (Fig. 5l), GRL-WHWP (Fig. 5m), NEU-IOD (Fig. 5n), NEU-WHWP (Fig. 5o), WNA-Niño 4 (Fig. 5w), and WNA-PMM (Fig. 5y) pairs. It is also concluded that the LSCOIs in the pairs of ENA-IOD (Fig. 5h), ENA-PMM (Fig. 5i), and ENA-WHWP (Fig. 5k) experience a clear lagging (i.e. arrows looking downward); and in pairs of CAS-IOD (Fig. 5b), ENA-TSA (Fig. 5j), SAF-IOD (Fig. 5p), SAF-WHWP (Fig. 5q), SSA-PDO (Fig. 5r), WAF-ALBSA (Fig. 5s), WNA-AMM (Fig. 5u), and WNA-IOD (Fig. 5v) experience leading effect (i.e. arrows looking upward).

The results further indicate that more recent TWSA contents (larger values in horizontal axis defining more recent times) exhibit stronger interconnections with low-frequency rates, suggesting that LSCOIs have a greater impact on terrestrial water content in the selected regions.

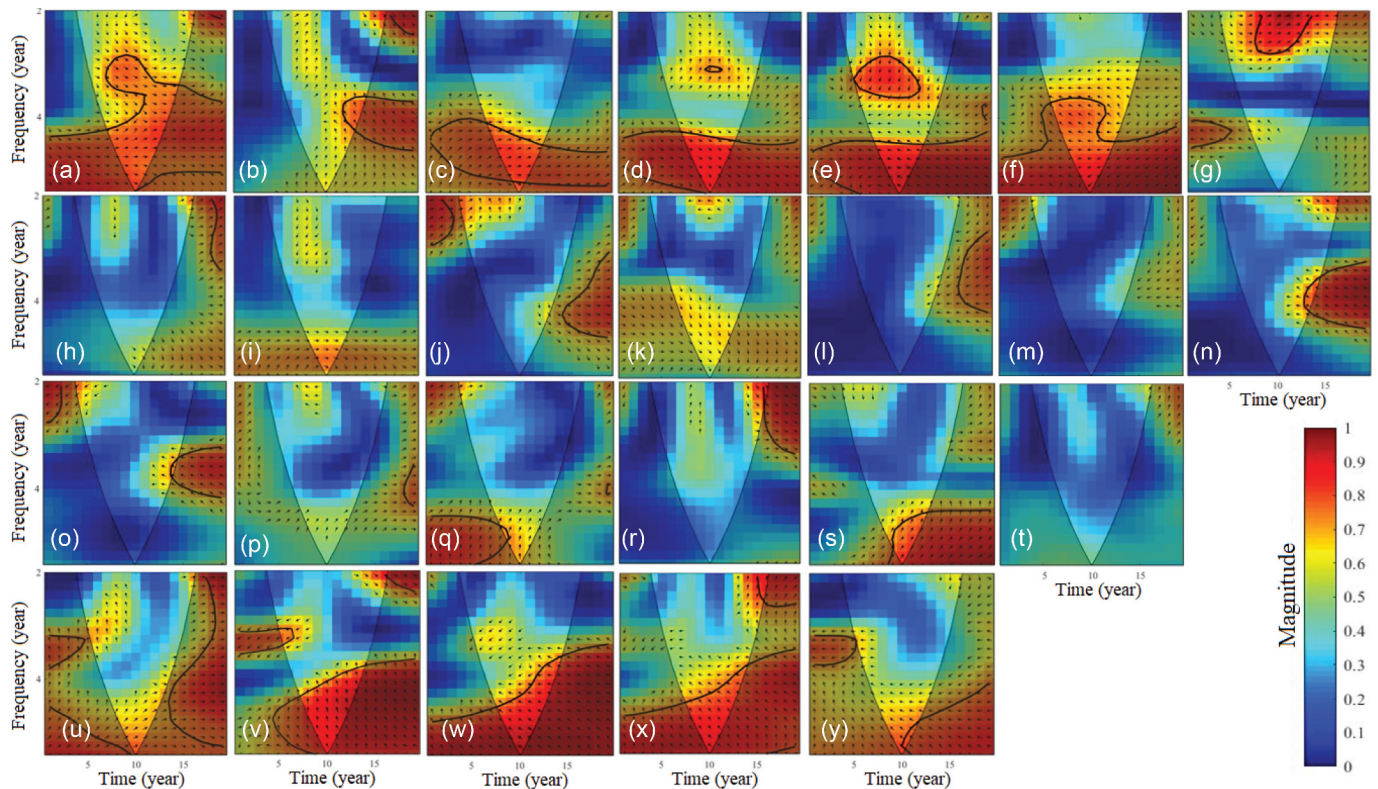


Figure 5. Results of the WCT between the (a) CAS-AMM, (b) CAS-IOD, (c) EAS-EN/NP, (d) EAS-Niño 4, (e) EAS-SOI, (f) EAS-TNI, (g) ENA-ALBSA, (h) ENA-IOD, (i) ENA-PMM, (j) ENA-TSA, (k) ENA-WHWP, (l) GRL-IOD, (m) GRL-WHWP, (n) NEU-IOD, (o) NEU-WHWP, (p) SAF-IOD, (q) SAF-WHWP, (r) SSA-PDO, (s) WAF-ALBSA, (t) WAF-IOD, (u) WNA-AMM, (v) WNA-IOD, (w) WNA-Niño 4, (x) WNA-PDO, and (y) WNA-PMM. (Colour bar depicts the intensity of the relationship; direction of the arrows shows the lagging and leading effect, and the blurred area depicts area that should be avoided due to noise effects).

3.4 Applicability of the results

As detailed previously, the RF and M5T models were used to further justify and validate the performed analyses and demonstrate the practical application of identified teleconnections. Based on the rationale explained earlier for employing these models, we implemented them using only the LSCOs with significant correlations (i.e. dominant effect), and their performance metrics are presented in Table 4.

Based on the results obtained from the evaluation metrics at both the training and testing stages, it can be inferred that the degree of linear dependence established between TWSA and LSCOs is not temporally stable (this can be confirmed in WCT analyses as well). Accordingly, the RF model demonstrated more promising performance, whereas, as expected, the evaluation metrics indicated a decline in predictive capability during the testing phase. Given that RF leverages bootstrapping and the randomization of datasets, it can be concluded that the establishment of linear dependence between TWSA and LSCOs is influenced by temporal variations and unidentified factors. Nevertheless, the relatively high correlation coefficients (r -values), coupled with reasonably low bias as reflected by MAE and RMSE values, suggest that the model maintains a satisfactory level of predictive accuracy.

In the training phase, RF consistently outperformed M5T across all regions, with higher correlation coefficients (r ranging from 0.86 to 0.97) and lower error metrics (e.g. in terms of MAE). However, the testing phase shows that the two models demonstrated different performance patterns across the various regions. Particularly remarkable is the performance in NEU, where M5T achieved an impressive test correlation of 0.98, surpassing RF's 0.93 during the test phase. The SAF

region showed robust prediction capability with both models achieving identical test correlations ($r = 0.91$), though M5T exhibited slightly lower error metrics. The varying performance across regions suggests that regional hydro-climatic characteristics and their relationships with LSCOs influence model efficacy, with some regions demonstrating stable teleconnection patterns (reflected in strong test correlations) while others show more complex or temporally variable relationships between climate oscillations and water storage anomalies.

4 Discussion

The study aims to examine the interrelations between LSCOs and TWSA in 12 pre-defined regions at continental and sub-continental level. Given the dependence of surface and subsurface water storage on historical precipitation and climatic responses, the investigation of teleconnections between TWSA and LSCO pairs becomes crucial. The analysis reveals that the selected variables can be categorized into two primary factors, collectively explaining a minimum of 50% of the total variance in the phase-space. Notably, the degree of interrelationships exhibits substantial variability, attributable to the intricate interactions and phase shifts of large-scale and semi-periodic oscillations in time and space. In this regard, the PCA could explain about 72.5%, 81.9%, 49.3%, 73.9%, 61.1%, 64.5%, 74.9%, 59.6%, 66.4%, 69.2%, 57.9%, and 66.2% of the total teleconnection volatilities in AMZ, SAU, CAS, EAS, ENA, GRL, NAS, NEU, SAF, SSA, WAF, and WNA, respectively.

The IOD and WHWP oscillations emerge as the preeminent climatic factors, demonstrating dominance in impacting

Table 4. Comparison of RF and M5T model performance metrics for predicting TWSA across different regions during training and testing phases.

Region	Metrics	Train		Test	
		RF	M5T	RF	M5T
CAS	MAE	2.49	3.59	2.80	2.01
	RMSE	2.79	4.31	3.18	2.45
	r	0.90	0.70	0.67	0.83
EAS	MAE	0.31	0.41	0.49	0.41
	RMSE	0.36	0.51	0.58	0.52
	r	0.89	0.70	0.52	0.33
ENA	MAE	0.73	1.34	1.15	1.15
	RMSE	0.90	1.63	1.29	1.34
	r	0.97	0.82	0.91	0.85
GRL	MAE	6.50	9.82	9.62	8.69
	RMSE	7.57	11.6	11.40	9.42
	r	0.93	0.75	0.68	0.83
NEU	MAE	1.58	2.62	2.26	2.36
	RMSE	1.84	3.10	2.73	2.94
	r	0.93	0.61	0.93	0.98
SAF	MAE	0.41	0.61	0.44	0.37
	RMSE	0.48	0.72	0.47	0.40
	r	0.94	0.68	0.91	0.91
SSA	MAE	0.55	0.82	0.7	1.2
	RMSE	0.71	1.13	0.77	1.43
	r	0.86	0.56	0.74	0.6
WAF	MAE	0.4	0.64	0.6	0.77
	RMSE	0.45	0.77	0.79	0.9
	r	0.94	0.69	0.74	0.85
WNA	MAE	0.73	1.46	1.58	1.67
	RMSE	1.15	1.87	1.85	1.97
	r	0.94	0.76	0.54	0.44

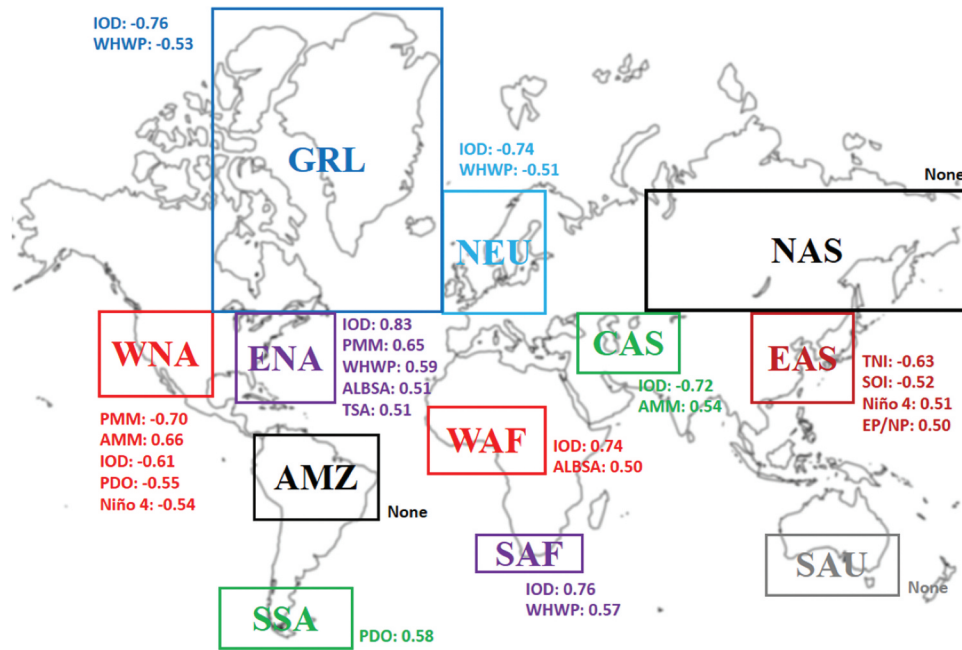


Figure 6. Effective ($|r| \geq 0.3$) and dominant ($|r| \geq 0.5$) oscillations based on the pair of TWSA-LSCOI correlation coefficient ranks.

TWSAs within the CAS ($r = -0.72$), ENA ($r = 0.82$), GRL ($r = -0.76$), NEU ($r = -0.74$), SAF ($r = 0.76$), WAF ($r = 0.74$), and WNA ($r = -0.61$); and ENA ($r = 0.59$), GRL ($r = -0.53$), NEU ($r = -0.51$), and SAF ($r = 0.55$) regions, respectively, substantiated by its high correlation coefficient. Figure 6 visually depicts the dominant interrelationship map (i.e. teleconnections), showcasing the global connections between TWSA and LSCOI indices. The results underscore the heightened oscillatory patterns observed in regions proximate to the Pacific and the Indian Oceans, suggesting their greater susceptibility to climatic influences. Particularly in equatorial regions, characterized by the convergence of numerous climatic factors, the interconnections between TWSA and climatic oscillations exhibit pronounced strength, accentuating the significance of these regions in the intricate dynamics of global water resources. This is in line with the preliminary studies of Okay Ahi and Jin (2019) who determined an effective linkage as high as 0.3 between GRACE-TWSA and ENSO index in the Mediterranean region. Yet, as detailed previously, the effectiveness of Niño 4 near Australian coasts compared to the Niño 1 + 2, Niño 3, and Niño 3.4 indices give credit to the eligibility and applicability of performing analyses on these indices separately, while other studies underline interdependence between climatic indices (e.g. Chen *et al.* 2014, Cheng *et al.* 2023, 2024).

The WCT analyses undertaken in this study reveals a discernible trade-off in the significance of teleconnection between TWSA and LSCOIs, thereby corroborating the earlier findings by Guo *et al.* (2021). The research emphasized the pivotal role played by the combined interconnections of these variables in determining the magnitude of response and temporal lag of total water content anomalies on a global scale. In the southern Hemisphere, encompassing the AMZ, SAF, and SAU regions, the analyses uncover a prevalent lagging effect of LSCOIs, coupled with an in-phase relationship observed among TWSA-LSCOI

pairs at low frequencies. However, a discernible leading effect emerges in TWSA patterns at high frequencies. In the more complex context of the northern Hemisphere, a noteworthy variation in the trade-off between lag and lead responses is observed, highlighting the intricate dynamics at play. Nonetheless, a robust conclusion can be drawn that lower frequencies of LSCOIs are gaining prominence globally, signifying an escalated frequency of extreme events. This trend can potentially be attributed to recent anthropogenic activities, which have significantly accelerated the pace of global climate change, as further corroborated by the research conducted by Liu *et al.* (2020).

Further evaluations indicate that the findings of this study are broadly consistent with those of Guo *et al.* (2021), particularly regarding the influence of time lags and phase relationships between LSCOIs and TWSAs. Their results suggest that, during the 2003–2016 period, the effects of ENSO, AMO, PDO, and IOD were especially relevant to TWSA variability. In a similar vein, Ndehedehe *et al.* (2017) explored the relationship between climate teleconnections and terrestrial water storage in West Africa. Their study found that ENSO, IOD, and AMO significantly affect regional water resources, with AMO exhibiting a notably strong correlation ($r = 0.62$) with the standardized precipitation index. Forootan *et al.* (2019) provided a global perspective by assessing hydrological droughts from 2003 to 2016 and analyzing their associations with major climate oscillations. Their findings highlighted significant links between TWSA fluctuations and teleconnection patterns, particularly illustrating the influence of ENSO, NAO, and IOD on drought conditions across various regions. More recently, Dong *et al.* (2024) underscored the roles of AMO, ENSO, the East Asian Summer Monsoon (EASM), and IOD as critical drivers of drought occurrence in China. They noted that, although statistically significant correlations and lead-lag relationships emerge at different timescales, the

interactions among these climate modes may be synergistic, neutral, or antagonistic in nature.

The limitations of this study however, primarily stem from several key aspects, including its applicability to broader continental and subcontinental regions, the incorporation of a more extensive set of LSCOs, extending the analyses and discussion based on the physical and behavioural patterns of the LSCOs, and the integration of nonlinear analytical techniques. Analyzing the persistence and memory of the system may also offer valuable insights for future research, as Berghuijs *et al.* (2025) demonstrated that, at annual timescales, precipitation patterns generally exhibit low persistence and system memory, whereas TWSA show a pronounced degree of temporal dependence. Additionally, the study could be further enhanced by incorporating Representative Concentration Pathways (RCPs) to assess the implications of climate change scenarios and trend extrapolations. Furthermore, the influence of data embedding and the coarse of dimensionality in the phase-space remains an area requiring deeper exploration, as these factors play a critical role in the accuracy and robustness of the analytical models.

5 Conclusion

In this study, we selected GRACE-based TWSA contents from the Amazon, Central Asia, East Asia, Eastern North America, Greenland, North Asia, Northern Europe, South Africa, Southern Australia, Southern South America, Western Africa, and Western North America for comparison against 25 climatic indices. The analyses were conducted at annual scales over the period of 2002–2020. To establish the teleconnections between each pair of TWSA-LSCO, we initially used correlation coefficients, defining effective ($|r| \geq 0.3$) and dominant ($|r| \geq 0.5$) relationships. These teleconnections were then subjected to PCA, WCT, and model development. Our findings lead to several conclusions:

- (1) IOD, AMM, WHWP, and TNI have exhibited a leading role in influencing TWSA in the northern Hemisphere, while TNI and WHWP have shown prominence in the southern Hemisphere.
- (2) The Pacific and Indian Oceans exert a significant influence on TWSA content worldwide.
- (3) In the southern Hemisphere, low-frequency oscillations exhibit a lagging effect along with an in-phase interrelationship.
- (4) Recently, high-frequency LSCOs have gained dominance, potentially indicating an escalation of climate change events.
- (5) Our analyses have explained about 50% to 82% of the events related to the TWSA records at AMZ, SAU, CAS, EAS, ENA, GRL, NAS, NEU, SAF, SSA, WAF, and WNA regions.
- (6) RF and M5T models' results confirm the significance and application of the conducted analyses to a great extent, while similar models can be used and/or developed based on the data analyses provided here in advance.

The findings of this study further validate our core understanding of LSCOs and their consequential effects on local and global climate variability. Specifically, LSCOs represent long-lasting and long-term oscillations with changing phases that significantly impact water content over time and space. However, we acknowledge several limitations in this study. These include the relatively limited length of the time series, the number of LSCOs considered, the number of case regions examined, multi-collinearity/inter-dependence among climate indices resulting in uncertainty, and the omission of temporal changes attributed to climate change. These limitations stem from the inherent diversity of climate patterns and the challenges associated with accessing comprehensive data for incorporation in our study. As a result, we encourage further research to explore the roles of additional LSCOs and the effects of shorter time periods (e.g. seasons, cycles, and months) across various regions globally.

Acknowledgements

The authors want to express their gratitude to Babak Farjad, who dedicated his time and expertise in performing analyses and development of the core idea of the study, and Ala Bahrami, Editor, and the anonymous reviewers for their insightful comments and helping us in upgrading our manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Babak Vaheddoost  <http://orcid.org/0000-0002-4767-6660>

Babak Mohammadi  <http://orcid.org/0000-0001-8427-5965>

Author Contributions

Babak Vaheddoost: conceptualization, methodology, software, validation, formal analyses, investigation, resources, data curation, writing --original draft preparation, writing --review and editing, visualization, supervision. **Babak Mohammadi:** conceptualization, methodology, validation, investigation, resources, data curation, writing --original draft preparation, writing --review and editing, project administration.

Application of the AI in the manuscript

The authors used ChatGPT for further proofreading and grammar checks in the text and all content was thoroughly reviewed and verified by the authors to ensure scientific accuracy.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

References

- Afamondji, K.M.C., *et al.*, 2025. Climate extreme indices influencing GRACE total water storage (TWS) in semi-arid Africa. *Journal of Arid Environments*, 229, 105357. doi:[10.1016/j.jaridenv.2025.105357](https://doi.org/10.1016/j.jaridenv.2025.105357)

- Akbas, A. and Ozdemir, H., 2023. Influence of atmospheric circulation on the variability of hydroclimatic parameters in the Marmara Sea river basins. *Hydrological Sciences Journal*, 68 (9), 1229–1240. doi:10.1080/02626667.2023.2206970
- Baldwin, M.P., et al., 2001. The quasi-biennial oscillation. *Reviews of Geophysics*, 39 (2), 179–229. doi:10.1029/1999RG000073
- Barnston, A.G. and Livezey, R.E., 1987. Classification, seasonality and persistence of low-frequency atmospheric circulation patterns. *Monthly Weather Review*, 115 (6), 1083–1126. doi:10.1175/1520-0493(1987)115<1083:CSAPOL>2.0.CO;2
- Barnston, A.G. and Livezey, R.E., 1987. Classification, seasonality and persistence of low-frequency atmospheric circulation patterns. *Monthly Weather Review*, 115 (6), 1083–1126. doi:10.1175/1520-0493(1987)115<1083:CSAPOL>2.0.CO;2
- Benaraba, N., et al., 2022. Jointly estimating recharge and groundwater withdrawals of the NWSAS by inverting GRACE/GRACE-FO gravity data. *Hydrological Sciences Journal*, 67 (15), 2215–2231. doi:10.1080/02626667.2022.2137416
- Berghuijs, W.R., et al., 2025. Annual memory in the terrestrial water cycle. *Hydrology and Earth System Sciences*, 29 (5), 1319–1333. doi:10.5194/hess-29-1319-2025
- Breiman, L., 2001. Random forests. *Machine Learning*, 45 (1), 5–32. doi:10.1023/A:1010933404324
- Bringeland, S. and Fotopoulos, G., 2024. Analysis of gap filling techniques for GRACE/GRACE-FO terrestrial water storage anomalies in Canada. *Journal of Hydrology*, 630, 130644. doi:10.1016/j.jhydrol.2024.130644
- Burn, D.H., 2008. Climatic influences on streamflow timing in the headwaters of the Mackenzie River Basin. *Journal of Hydrology*, 352 (1–2), 225–238. doi:10.1016/j.jhydrol.2008.01.019
- Chan, J.C. and Zhou, W., 2005. PDO, ENSO and the early summer monsoon rainfall over south China. *Geophysical Research Letters*, 32 (8). doi:10.1029/2004GL020215
- Chen, S., et al., 2024. Strengthened impact of boreal winter North Pacific Oscillation on ENSO development in warming climate. *Npj Climate and Atmospheric Science*, 7 (1), 69. doi:10.1038/s41612-024-00615-3
- Chen, S., Yu, B., and Chen, W., 2014. An analysis on the physical process of the influence of AO on ENSO. *Climate Dynamics*, 42 (3–4), 973–989. doi:10.1007/s00382-012-1654-z
- Cheng, X., et al., 2023. Observed impact of the Arctic Oscillation in boreal spring on the Indian Ocean Dipole in the following autumn and possible physical processes. *Climate Dynamics*, 61 (1–2), 883–902. doi:10.1007/s00382-022-06616-3
- Cheng, X., et al., 2024. Selective influence of the Arctic Oscillation on the Indian Ocean Dipole and El Niño–Southern Oscillation. *Climate Dynamics*, 62 (5), 3783–3798. doi:10.1007/s00382-023-07098-7
- Chiang, J.C. and Vimont, D.J., 2004. Analogous Pacific and Atlantic meridional modes of tropical atmosphere–ocean variability. *Journal of Climate*, 17 (21), 4143–4158. doi:10.1175/JCLI4953.1
- Cho, Y., 2024. Analysis of terrestrial water storage variations in South Korea using GRACE satellite and GLDAS data in google earth engine. *Hydrological Sciences Journal*, 69 (8), 1032–1045. doi:10.1080/02626667.2024.2351067
- Climate Variability: oceanic Niño Index | NOAA Climate.gov. <https://www.climate.gov/news-features/understanding-climate/climate-variability-oceanic-ni%C3%B1o-index>. [Accessed 29 July 2023c].
- Cox, C.J., et al., 2019. The aleutian low-beaufort sea anticyclone: a climate index correlated with the timing of springtime melt in the Pacific Arctic cryosphere. *Geophysical Research Letters*, 46 (13), 7464–7473. doi:10.1029/2019GL083306
- Doi, T., Tozuka, T., and Yamagata, T., 2010. The Atlantic meridional mode and its coupled variability with the Guinea Dome. *Journal of Climate*, 23 (2), 455–475. doi:10.1175/2009JCLI3198.1
- Dong, H., et al., 2024. Effects of interaction of multiple large-scale atmospheric circulations on precipitation dynamics in China. *Science of the Total Environment*, 923, 171528. doi:10.1016/j.scitotenv.2024.171528
- Enfield, D.B., et al., 1999. How ubiquitous is the dipole relationship in tropical Atlantic sea surface temperatures? *Journal of Geophysical Research: Oceans*, 104 (C4), 7841–7848. doi:10.1029/1998JC900109
- Extension to the North Atlantic oscillation using early instrumental pressure observations from Gibraltar and south-west Iceland - Jones - 1997 - International Journal of Climatology - Wiley Online Library. <https://rmets.onlinelibrary.wiley.com/doi/10.1002/%28SICI%291097-0088%2819971115%2917%3A13%3C1433%3A%3AAID-JOC203%3E3.0.CO%3B2-P>. [Accessed 29 July 2023].
- Fathian, F., Amini, M., and Vaheddoost, B., (2021). A quantile-based realization of the indirect-link between large-scale atmospheric oscillation and lake water level. *Arabian Journal of Geosciences*, 14 (24), 2721. doi:10.1007/s12517-021-08961-9
- Forootan, E., et al., 2019. Understanding the global hydrological droughts of 2003–2016 and their relationships with teleconnections. *Science of the Total Environment*, 650, 2587–2604. doi:10.1016/j.scitotenv.2018.09.231
- Gao, T., Wang, H.J., and Zhou, T., 2017. Changes of extreme precipitation and nonlinear influence of climate variables over monsoon region in China. *Atmospheric Research*, 197, 379–389. doi:10.1016/j.atmosres.2017.07.017
- Giorgi, F. and Francisco, R., 2000. Uncertainties in regional climate change prediction: a regional analysis of ensemble simulations with the HADCM2 coupled AOGCM. *Climate Dynamics*, 16 (2–3), 169–182. doi:10.1007/PL00013733
- Glantz, M.H. and Ramirez, I.J., 2020. Reviewing the Oceanic Niño Index (ONI) to enhance societal readiness for El Niño’s impacts. *International Journal of Disaster Risk Science*, 11 (3), 394–403. doi:10.1007/s13753-020-00275-w
- Gorugantula, S.S. and Kambhammettu, B.P., 2022. Sequential downscaling of GRACE products to map groundwater level changes in Krishna River basin. *Hydrological Sciences Journal*, 67 (12), 1846–1859. doi:10.1080/02626667.2022.2106142
- Greenacre, M., et al., 2022. Principal component analysis. *Nature Reviews Methods Primers*, 2 (1), 100. doi:10.1038/s43586-022-00184-w
- Grinsted, A., Moore, J.C., and Jevrejeva, S., 2004. Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Processes in Geophysics*, 11 (5/6), 561–566. doi:10.5194/npg-11-561-2004
- Guo, L., et al., 2021. Links between global terrestrial water storage and large-scale modes of climatic variability. *Journal of Hydrology*, 598, 126419. doi:10.1016/j.jhydrol.2021.126419
- Han, Z., et al., 2019. Assessing GRACE-based terrestrial water storage anomalies dynamics at multi-timescales and their correlations with teleconnection factors in Yunnan Province, China. *Journal of Hydrology*, 574, 836–850. doi:10.1016/j.jhydrol.2019.04.093
- Hurrell, J.W., 1995. Decadal trends in the North Atlantic Oscillation: regional temperatures and precipitation. *Science*, 269 (5224), 676–679. doi:10.1126/science.269.5224.676
- Kalra, A., et al., 2013. Improving streamflow forecast lead time using oceanic-atmospheric oscillations for Kaidu river basin, Xinjiang, China. *Journal of Hydrologic Engineering*, 18 (8), 1031–1040. doi:10.1061/(ASCE)HE.1943-5584.0000707
- Khorrami, B. and Gunduz, O., 2021. An enhanced water storage deficit index (EWSDI) for drought detection using GRACE gravity estimates. *Journal of Hydrology*, 603, 126812. doi:10.1016/j.jhydrol.2021.126812
- Kuhn, M., et al. (2025). Package ‘Cubist’. Rule-and Instance-Based Regression Modeling. R Package Version 0.4.4. doi: 10.32614/CRAN.package.Cubist
- Kumar, P., et al., 2020. 20th century multivariate Indian Ocean regional sea level reconstruction. *Journal of Geophysical Research: Oceans*, 125 (10), e2020JC016270. doi:10.1029/2020JC016270
- Kundzewicz, Z.W., Szwed, M., and Pińskwar, I., 2019. Climate variability and floods—A global review. *Water*, 11 (7), 1399. doi:10.3390/w11071399
- Kuss, A.J.M. and Gurdak, J.J., 2014. Groundwater level response in U.S. principal aquifers to ENSO, NAO, PDO, and AMO. *Journal of Hydrology*, 519, 1939–1952. doi:10.1016/j.jhydrol.2014.09.069
- Li, R., et al., 2015. Decadal oscillation of autumn precipitation in Central Vietnam modulated by the East Pacific–North Pacific (EP–NP) teleconnection. *Environmental Research Letters*, 10 (2), 024008. doi:10.1088/1748-9326/10/2/024008
- Li, X., et al., 2024. Investigation of 2020–2022 extreme floods and droughts in Sichuan Province of China based on joint inversion of GNSS and GRACE/GFO data. *Journal of Hydrology*, 632, 130868. doi:10.1016/j.jhydrol.2024.130868

- Linderholm, H.W., *et al.*, 2011. Interannual teleconnections between the summer North Atlantic Oscillation and the East Asian summer monsoon. *Journal of Geophysical Research: Atmospheres*, 116 (D13). doi:10.1029/2010JD015235
- Liu, D., *et al.*, 2021. Support vector machine and data assimilation framework for Groundwater Level Forecasting using GRACE satellite data. *Journal of Hydrology*, 603, 126929. doi:10.1016/j.jhydrol.2021.126929
- Liu, X., *et al.*, 2020. Widespread decline in terrestrial water storage and its link to teleconnections across Asia and Eastern Europe. *Hydrology and Earth System Sciences*, 24 (7), 3663–3676. doi:10.5194/hess-24-3663-2020
- Mahmoudi, M.H., Najafi, M.R., and Abbasian, M.S., 2022. Influence of low frequency variability modes on spatiotemporal patterns of temperature and precipitation in Northwestern North America. *Hydrological Sciences Journal*, 67 (13), 2002–2013. doi:10.1080/02626667.2022.2121166
- Mantua, N.J., *et al.*, 1997. A Pacific interdecadal climate oscillation with impacts on salmon production. *Bulletin of the American Meteorological Society*, 78 (6), 1069–1080. doi:10.1175/1520-0477(1997)078<1069:APICOW>2.0.CO;2
- Maraun, D., Kurths, J., and Holschneider, M., 2007. Nonstationary Gaussian processes in wavelet domain: synthesis, estimation, and significance testing. *Physical Review E—Statistical, Nonlinear, and Soft Matter Physics*, 75 (1), 016707. doi:10.1103/PhysRevE.75.016707
- Mohammadi, B., Vaheddoost, B., and Mehr, A.D., 2020. A spatiotemporal teleconnection study between Peruvian precipitation and oceanic oscillations. *Quaternary International*, 565, 1–11. doi:10.1016/j.quaint.2020.09.042
- Morlet, J., *et al.*, 1982. Wave propagation and sampling theory—Part I: complex signal and scattering in multilayered media. *Geophysics*, 47 (2), 203–221. doi:10.1190/1.1441328
- Ndehedehe, C.E., *et al.*, 2017. Climate teleconnections influence on West Africa's terrestrial water storage. *Hydrological Processes*, 31 (18), 3206–3224. doi:10.1002/hyp.11237
- Okay Ahi, G. and Jin, S., 2019. Hydrologic mass changes and their implications in Mediterranean-climate Turkey from GRACE measurements. *Remote Sensing*, 11 (2), 120. <https://www.mdpi.com/2072-4292/11/2/120>
- Pereira, A., *et al.*, 2024. Assessing water storage variations in La Plata basin and sub-basins from GRACE, global models data and connection with ENSO events. *Hydrological Sciences Journal*, 69, 1012–1031. doi:10.1080/02626667.2024.2349277
- Quinlan, J.R. (1992). Learning with continuous classes. In *The 5th Australian joint conference on artificial intelligence (AICAI5)*, 16 to 18 November 1992 Hobart, Tasmania, 92, 343–348.
- Quinlan, J.R. (1993). Combining instance-based and model-based learning. In *The 10th international conference on machine learning (ICML 1993)*, June 27–29, 1993 Amherst, Massachusetts, USA, 236–243.
- Rayner, N.A., *et al.*, 2003. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late 19th century. *Journal of Geophysical Research: Atmospheres*, 108 (D14). doi:10.1029/2002JD002670
- Ringnér, M., 2008. What is principal component analysis? *Nature Biotechnology*, 26 (3), 303–304. doi:10.1038/nbt0308-303
- Ropelewski, C.F. and Jones, P.D., 1987. An Extension of the Tahiti–Darwin Southern Oscillation Index. *Monthly Weather Review*, 115 (9), 2161–2165. doi:10.1175/1520-0493(1987)115<2161:AEOTTS>2.0.CO;2
- Sanchez-Rubio, G., *et al.*, 2011. Oceanic–atmospheric modes of variability and their influence on riverine input to coastal Louisiana and Mississippi. *Journal of Hydrology*, 396 (1–2), 72–81. doi:10.1016/j.jhydrol.2010.10.034
- Schneider, D.P., *et al.*, 2013. Climate data guide spurs discovery and understanding. *Eos, Transactions American Geophysical Union*, 94 (13), 121–122. doi:10.1002/2013EO130001
- Schwing, F.B., Murphree, T., and Green, P.M., 2002. The Northern Oscillation Index (NOI): a new climate index for the northeast Pacific. *Progress in Oceanography*, 53 (2–4), 115–139. doi:10.1016/S0079-6611(02)00027-7
- Sheffield, J., *et al.*, 2018. Satellite Remote Sensing for Water Resources Management: potential for Supporting Sustainable Development in Data-Poor Regions. *Water Resources Research*, 54 (12), 9724–9758. doi:10.1029/2017WR022437
- Shi, P., *et al.*, 2016. Large-scale climate patterns and precipitation in an arid endorheic region: linkage and underlying mechanism. *Environmental Research Letters*, 11 (4), 044006. doi:10.1088/1748-9326/11/4/044006
- Singh, S., *et al.*, 2015. Baseflow response to climate variability induced droughts in the Apalachicola–Chattahoochee–Flint River Basin, U.S.A. *Journal of Hydrology*, 528, 550–561. doi:10.1016/j.jhydrol.2015.06.068
- Sohrabi, S., Brissette, F.P., and Arsenault, R., 2021. Coupling large-scale climate indices with a stochastic weather generator to improve long-term streamflow forecasts in a Canadian watershed. *Journal of Hydrology*, 594, 125925. doi:10.1016/j.jhydrol.2020.125925
- Sun, P., Guo, C., and Wei, D., 2023. Estimating terrestrial water storage variations in Chile with the effects of earthquakes deducted. *Hydrological Sciences Journal*, 68 (12), 1663–1679. doi:10.1080/02626667.2023.2230217
- Tapley, B.D., *et al.*, 2019. Contributions of GRACE to understanding climate change. *Nature Climate Change*, 9 (5), 358–369. doi:10.1038/s41558-019-0456-2
- Terrestrial Hydrosphere | earthdata. 2023. <https://www.earthdata.nasa.gov/topics/terrestrial-hydrosphere>. [Accessed 29 July 2023a]
- Torrence, C. and Compo, G.P., 1998. A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, 79 (1), 61–78. doi:10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2
- Torrence, C. and Webster, P.J., 1999. Interdecadal changes in the ENSO–monsoon system. *Journal of Climate*, 12 (8), 2679–2690. doi:10.1175/1520-0442(1999)012<2679:ICITEM>2.0.CO;2
- Trenberth, K.E. and Hurrell, J.W., 1994. Decadal atmosphere–ocean variations in the Pacific. *Climate Dynamics*, 9 (6), 303–319. doi:10.1007/BF00204745
- Trenberth, K.E. and Stepaniak, D.P., 2001. Indices of el Niño evolution. *Journal of Climate*, 14 (8), 1697–1701. doi:10.1175/1520-0442(2001)014<1697:LIOENO>2.0.CO;2
- Vaheddoost, B., 2017. Spatial Analysis of Large Atmospheric Oscillations and Annual Precipitation in Lake Urmia Basin. *European Water*, 59, 123–129.
- Vaheddoost, B., 2020. A Spatiotemporal Classification of the Peruvian Precipitations Between 1990 and 2015. *Pure and Applied Geophysics*, 177 (9), 4509–4520. doi:10.1007/s00024-020-02454-8
- Wang, C. and Enfield, D.B., 2001. The tropical Western Hemisphere warm pool. *Geophysical Research Letters*, 28 (8), 1635–1638. doi:10.1029/2000GL011763
- West, H., Quinn, N., and Horswell, M., 2022. Spatio-temporal propagation of North Atlantic Oscillation (NAO) rainfall deviations to streamflow in British catchments. *Hydrological Sciences Journal*, 67 (5), 676–688. doi:10.1080/02626667.2022.2038791
- Wrzesiński, D. and Paluszkiwicz, R., 2011. Spatial differences in the impact of the North Atlantic Oscillation on the flow of rivers in Europe. *Hydrology Research*, 42 (1), 30–39. doi:10.2166/nh.2010.077
- Xie, J., *et al.*, 2022. Understanding the impact of climatic variability on terrestrial water storage in the Qinghai–Tibet Plateau of China. *Hydrological Sciences Journal*, 67 (6), 963–978. doi:10.1080/02626667.2022.2044482
- Xu, Z., *et al.*, 2021. Detecting and quantifying the impact of long-term terrestrial water storage changes on the runoff ratio in the head regions of the two largest rivers in China. *Journal of Hydrology*, 601, 126668. doi:10.1016/j.jhydrol.2021.126668
- Yang, F., *et al.*, 2024. A Monte Carlo propagation of the full variance-covariance of GRACE-Like level-2 data with applications in hydrological data assimilation and sea-level budget studies. *Water Resources Research*, 60 (9), e2023WR036764. doi:10.1029/2023WR036764
- Yang, R., Xie, Z., and Cao, J., 2017. A dynamic index for the westward ridge point variability of the western Pacific subtropical high during summer. *Journal of Climate*, 30 (9), 3325–3341. doi:10.1175/JCLI-D-16-0434.1
- Yoshe, A.K., 2024. Water availability identification from GRACE dataset and GLDAS hydrological model over data-scarce river basins of

- Ethiopia. *Hydrological Sciences Journal*, 69 (6), 721–745. doi:[10.1080/02626667.2024.2333852](https://doi.org/10.1080/02626667.2024.2333852)
- Zhang, H., *et al.*, 2021. Investigation about the correlation and propagation among meteorological, agricultural and groundwater droughts over humid and arid/semi-arid basins in China. *Journal of Hydrology*, 603, 127007. doi:[10.1016/j.jhydrol.2021.127007](https://doi.org/10.1016/j.jhydrol.2021.127007)
- Zhang, W., Jin, -F.-F., and Turner, A., 2014. Increasing autumn drought over southern China associated with ENSO regime shift. *Geophysical Research Letters*, 41 (11), 4020–4026. doi:[10.1002/2014GL060130](https://doi.org/10.1002/2014GL060130)
- Zheng, Y., *et al.*, 2023. A continuing increase of the impact of the spring North Pacific meridional mode on the following winter El Niño and Southern Oscillation. *Journal of Climate*, 36 (2), 585–602. doi:[10.1175/JCLI-D-22-0190.1](https://doi.org/10.1175/JCLI-D-22-0190.1)
- Zheng, Y., *et al.*, 2024. The role of the Aleutian Low in the relationship between spring Pacific Meridional Mode and following ENSO. *Journal of Climate*, 37 (11), 3249–3268. doi:[10.1175/JCLI-D-23-0440.1](https://doi.org/10.1175/JCLI-D-23-0440.1)
- Zheng, Y., Chen, W., and Chen, S., 2021. Intermodel spread in the impact of the Springtime Pacific Meridional mode on following-winter ENSO tied to simulation of the ITCZ in CMIP5/CMIP6. *Geophysical Research Letters*, 48 (17), e2021GL093945. doi:[10.1029/2021GL093945](https://doi.org/10.1029/2021GL093945)
- Zhou, Q., *et al.*, 2022. Spatial-temporal changes to GRACE-derived terrestrial water storage in response to climate change in arid Northwest China. *Hydrological Sciences Journal*, 67 (4), 535–549. doi:[10.1080/02626667.2022.2030060](https://doi.org/10.1080/02626667.2022.2030060)
- Zhou, S., *et al.*, 2001. Trends of NAO and AO and their associations with stratospheric processes. *Geophysical Research Letters*, 28 (21), 4107–4110. doi:[10.1029/2001GL013660](https://doi.org/10.1029/2001GL013660)